Production Risk, Pesticide Use and GM Crop Technology in South Africa

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Abstract:

Technology involving genetic modification of crops has the potential to make a contribution to rural poverty reduction in many developing countries. Thus far, pesticide-producing 'Bt' varieties of cotton have been the main GM crops under cultivation in developing nations. Several studies have evaluated the farm-level performance of Bt varieties in comparison to conventional ones by estimating production technology, and have mostly found Bt technology to be very successful in raising output and/or reducing pesticide input. However, the production risk properties of this technology have not been studied, although they are likely to be important to risk-averse smallholders. This study investigates the output risk aspects of Bt technology by estimating two 'flexible risk' production function models allowing technology to independently affect the mean and higher moments of output. The first is the popular Just-Pope model and the second is a more general 'damage control' flexible risk model. The models are applied to cross-sectional data on South African smallholders, some of whom used Bt varieties. The results show no evidence that a 'risk-reduction' claim can be made for Bt technology. Indeed, there is some evidence to support the notion that the technology increases output risk, implying that simple (expected) profit computations used in past evaluations may overstate true benefits.

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I. Introduction

Genetically Modified (GM) crop technology is a potentially powerful addition to the toolkit for poverty alleviation in rural areas of developing countries. GM technology may provide answers to agricultural problems that conventional plant breeding methods have not been able to address adequately in the developing world (Nuffield Council for Bioethics (2003)). The promise held out is not restricted to larger, richer farmers; Given appropriate institutional conditions, GM technology is also seen as being capable of benefiting small, resource-poor farmers (FAO, 2004).

Bacillus Thuringensis (Bt) varieties of cotton and maize, first commercialized by Monsanto, Inc., are now the most widespread types of GM crops in the developing world. The Bt gene contained in Bt varieties produces a natural insecticide that acts specifically on a class of troublesome pests (notably bollworms) that regularly decimate crops in developing countries. Since its introduction in South Africa in 1998, Bt varieties, particularly of cotton, have been taken up by farmers in several other developing countries, notably the extremely populous and largely rural China and India.

Rigorous farm-level performance evaluation of the first generation of Bt varieties has been conducted in the main adopting countries, and this first generation of results by and large indicate that Bt technology has been a noteworthy success. Two types of benefits have been reported, pesticide reduction and yield increase. In China, the extant level of pesticide use in cotton is very high, and pesticides are generally thought to be overused (applied beyond the economic optimum). In this case, the contribution of the Bt variety has been to enable a substantial reduction in pesticide (over)use, with only a marginal effect on yields. These results have been reported and analyzed in Pray, *et. al.* (2001) and Huang, *et. al.* (2003). On the other hand, in South Africa and India, pesticide inputs are more likely to be underused (applied below the economic optimum) due to credit and labour availability constraints and market failure problems associated with the availability of timely supplies. Here, the contribution of the Bt variety has been to increase yields substantially, with modest changes in pesticide use. These results are reported and discussed in, among others, Qaim and Zilberman (2003); Thirtle, *et. al.* (2002); Shankar and Thirtle (2005); Qaim (2003); Qaim and de Janvry (2005).

All the studies mentioned above have undertaken their farm-level performance evaluation via the estimation of production technology, with a dummy variable representation for the use of Bt technology. Standard production functions have been estimated, in Qaim (2003), Qaim and Zilberman (2003) and Qaim and de Janvry (2005). 'Damage Control' production functions, which account for the special, damage abating nature of pesticide inputs and Bt technology, have been used in all the previous studies with the exception of Thirtle *et. al.* (2002). Thirtle *et. al.* instead used a stochastic frontier representation of technology. Almost without exception, these studies indicate superior performance of Bt varieties relative to local counterparts.

Valuable as the information contained in these studies is, it is important to note that the representations of production technology used in the above studies do not consider the production risk element. Agricultural production is inherently risky, and smallholders in developing countries are likely very risk-averse. More complete production impact evaluation of inputs and technologies will therefore need consideration of their interactions with the riskiness of output. Thus it has been long recognized in the agricultural economics literature that it is important to allow inputs, particularly pesticides (and therefore technologies that embody pesticides, such as Bt), to freely affect variance and higher moments of output.

However, typically employed production functions, such as the Quadratic and the Cobb-Douglas, do not allow production inputs and technologies to flexibly affect variance and higher moments of output (Just and Pope, 1979). This is also true of the standard damage control production functions (Saha, *et. al.*, 1997) and stochastic frontier functions (Battese, Rambaldi and Wan, 1997). Thus these studies only consider the effect of technology on the expected value of output.

The objective of this paper is to help reduce this gap in knowledge about the production risk impact of Bt technology[1]. It accomplishes this by applying two 'flexible risk' production function models to the South African cotton smallholder data previously reported in Thirtle *et. al.* (2002) and Shankar and Thirtle (2005). The first model, which applies a Just-Pope production function (Just and Pope, 1979) to the data, is seen as a preliminary step prior to the application of a second, more complex model. This second model is an adaptation of Saha *et. al.*'s (1997) model which incorporates flexible risk properties while retaining the 'damage control' representation of pesticides and Bt technology. From both models, we simply wish to test the hypothesis that Bt technology reduces yield (output) risk. To our knowledge, no previous studies have empirically measured the production risk properties of Bt technology in a developing country setting.

If the risk-reduction hypothesis is confirmed, GM technology can be said to possess an additional 'insurance' function beyond the pesticide reduction/yield increase attributes analyzed before. The benefits from the technology would then include a positive risk premium obtained in addition to benefits (expected value of profits) obtained from mean output increases. On the other hand, a risk-increasing result would imply that computed profits overstate the true benefits from the technology. Thus the study of the risk properties is important for more complete impact evaluation of Bt technology.

Section II proceeds by considering the analytic insights available from previous literature on how pesticides, and thus Bt technology, may affect risk. Section III sets out the empirical framework, and section IV presents and discusses the results. Section V concludes and offers suggestions for future work.

II. Analytical Background

The simple bioeconomics of pesticides and risk

Bt technology embodies a pesticide, and hence notions relating to the risk effects of Bt technology are parallel to those concerning conventional pesticides. While there is intuitive appeal on the surface to suggest that pesticides should decrease risk, Pannell (1991) suggests that this is misleading, and several empirical studies instead find a risk-increasing effect (*eg.* Antle (1988); Horowitz and Lichtenberg (1993)). Horowitz and Lichtenberg (1994) provide an elegant exposition explaining why a risk-increasing effect is at least as plausible as a risk-decreasing effect. We lean heavily on their exposition in heuristically outlining the arguments below.

Consider a production function, $f(z, \mathbf{x}, e)$, where z is pesticide input, $\mathbf{x}$ is a vector of all other inputs, and e is random production error. Without loss of generality, suppose e is ordered from bad states of nature to good states of nature, implying $f_e(z, \mathbf{x}, e) > 0$ where the subscript denotes the partial derivative. We would expect pesticide to not decrease output in any state of nature, *i.e.*, $f_z(z, \mathbf{x}, e) > 0$. Risk averse producers may be characterized as choosing $(z, \mathbf{x})$ to solve Max $\int U(pf(z, \mathbf{x}, e) - w_z z - w_\mathbf{x}\mathbf{x})de$, where U(.) is the utility function, p is output price, w_z is pesticide price and $w_\mathbf{x}$ is the vector of other input prices. Then input z can be said to be risk-decreasing (increasing) if $f_{ze}(z, \mathbf{x}, e) < 0$, *i.e.*, z increases output more in bad (good) states of nature than in good (bad). Quiggin (1991) demonstrates that this definition is equivalent to alternative definitions of risk-decreasing (increasing) inputs used in the literature, such as that more risk-averse producers use more (less) of risk-decreasing (increasing) inputs than less risk averse producers, all else equal. If e mainly represented randomness of pest density, then we have the conventional wisdom that pesticide and Bt technology should be risk-decreasing, since they raise output more in bad states of nature, *i.e.*, when pest density is high.

Intuitive as this logic seems, Horowitz and Lichtenberg (1994) show that it is untenable when alternative or multiple sources of uncertainty are considered. In developing country agricultural situations such as the rainfed cotton cultivation case we consider, rainfall, or crop growth conditions more generally, are at least as important as sources of randomness as pest density. In a situation where pest density is relatively stable, but there is considerable uncertainty over rainfall, rainfall becomes the main source of randomness in e. In such a case, during the good states of nature (high rainfall) there is more crop to save given the pest density, and pesticides raise output more in this good state of nature, making pesticide a risk-increasing input. In many agricultural situations, both sources of randomness, pest density and rainfall, are important. More so, they are likely to be negatively correlated, *i.e.* pest density is high (bad state of nature with regard to pest density) when rainfall is high (good state of nature with regard to rainfall). In cases of strong negative correlation between these two, Horowitz and Lichtenberg's analysis suggests again that pesticides are likely to be risk-increasing.

Thus, we are able to take away two major lessons from this previous literature:

(i) The risk effect of pesticides and Bt-technology can differ from situation to situation, and is a matter for empirical determination in any given situation, and

(ii) It may be important to explicitly account for multiple sources of randomness in empirical analysis.

Note, however, that even though the above bioeconomic framework goes significantly beyond the standard production framework in its consideration of risk, ground realities can be more complex still. High rainfall may not always represent a good state of nature even in the absence of pest considerations. The effect would depend on the amount of rainfall at various stages of plant growth. Rainfall and pest control interactions may also be affected by considerations such as pesticide wash-off caused by high rainfall. In Makhathini, there is anecdotal evidence that the latter effect might have occurred in the season for which our analysis has been conducted. However, consideration of such effects requires much more detailed data than are available to us, and is thus beyond the scope of this paper. Work by Antle (1983; 1988) provides an example of how pest control input determination can be viewed as a sequential problem, and how data from multiple stages during the season can be used to enhance empirical production models.

Risk and damage abatement properties of production functions

Conventional production functions are incapable of displaying flexible risk properties. Production functions additive in the error term, such as the Quadratic, do not allow inputs to either decrease or increase risk. In other words, where $f(z, \mathbf{x}, e) = g(z, \mathbf{x}) + e$, $f_{ze} = 0$. Those with mutiplicative exponential error terms, such as the Cobb-Douglas and the Translog only allow risk-increasing effects, *i.e.*, where $f(z, \mathbf{x}, e) = g(z, \mathbf{x})\exp^{e}$, $f_{ze} > 0$. Apart from their inflexibility in allowing the data to determine risk properties, these production functions also lump all sources of randomness into a single error term. Another critical shortcoming for agricultural applications is that they treat all inputs symmetrically, not accounting for the special nature of inputs like pesticides. The last point is also true of 'stochastic production functions' such as the Just-Pope production functions, $y = q(z, \mathbf{x}) + h(z, \mathbf{x})e$, which are able to allow flexible risk properties, but do not account for the special, damage abating nature of pesticide inputs.

Lichtenberg and Zilberman (1986) presented a critique of traditional production functions, and offered an alternative, more intuitive way to model the role of pesticide in the agricultural production process. Drawing inspiration from the bioeconomic literature, they posited that pesticides belong to a class of 'damage control' inputs. Damage control inputs are different from conventional inputs in that they affect output only indirectly, by reducing the extent of damage in the event that damage occurs. In contrast, conventional inputs such as fertilizer and labour increase output directly.

If y denotes output, **x** is a vector of 'conventional' inputs, and z is the damage control (pesticide), then y = f(**x**, g(z)), with f(.) concave in **x** and g(z). g(z), the 'abatement function', is defined on the [0, 1] interval and is increasing in z. as z increases, $g(z) \to 1$ and $y \to f(x)$, *i.e.*, a greater part of maximum potential output is realized. As z decreases, $g(z) \to 0$, and $y \to f(x,0)$, i.e., output falls towards the level consistent with maximum destructive capacity. For reasons of econometric identification, the practice in empirical work is to simplify the damage control function to a proportional one, *i.e.*, y = f(x)g(z).

In the context of pest management, the above specification implies that as pesticide input z increases, abatement $g(z) \to 1$, and at the limit y = f(x), i.e., there is no destruction due to pest damage and maximum potential output is realized. As pesticide application declines towards 0, $g(z) \to 0$, and $y \to 0$. Since y is now proportional to g(z) and g(z) is between 0 and 1, g(z) represents the percentage of maximum potential output realized for a given level of pesticide use, z. Since g(z) lies in the [0,1] interval, a choice of several cumulative distribution functions is available to model g(z), with the Weibull, Exponential and Logistic widely used in applications. Where the damage control representation is appropriate, Lichtenberg & Zilberman demonstrate that using conventional specifications can lead to serious bias and erroneous conclusions about the productivity and use efficiencies of pesticides as well as the other conventional inputs included in the analysis.

As discussed before, most of the Bt cotton evaluation papers have accordingly used damage control specifications in their analysis. However, even though this corrects the potential bias caused by the special nature of pesticide inputs, it does not provide flexibility with regard to risk effects. It is easy to show that the usual damage control functions cannot allow mean and variance effects of inputs (or technologies) to be qualitatively independent of each other.

Damage control specification with flexible risk properties

The above discussion points to the need for a specification that allows a damage control characterization for pesticide and Bt technology, flexible risk properties for the input and the technology, and explicit accounting for multiple sources of uncertainty. Saha, Shumway and Havenner (1997) present such a model (henceforth referred to as the SSH model), which we use as the main basis for our empirical work. Their model is described briefly below.

The SSH production function is described by:

$$y = f(\mathbf{x}, \boldsymbol{\beta})\, g(\mathbf{z}, \boldsymbol{\alpha}, e) \exp(\varepsilon) \qquad (1)$$

Here, $\boldsymbol{\beta}$ is a vector of parameters attached to the 'conventional' inputs in $\mathbf{x}$, while $\boldsymbol{\alpha}$ is the parameter vector attached to the 'damage control' inputs in $\mathbf{z}$. A key difference relative to the ordinary damage control function specification is that (1) contains two error terms: e, attached to the damage control function g(.), that represents pest and pesticide application related randomness, and ε, related to randomness in crop growth conditions such as rainfall variability. e and ε are allowed to be correlated. The SSH model makes two key assumptions that facilitates the identification and estimation of the model: (i) The damage control function is specified as $g(\mathbf{z}, \boldsymbol{\alpha}, e) = \exp[-A(\mathbf{z}, \boldsymbol{\alpha})e]$, where A(.) is a continuous and differentiable function, and (ii) $\varepsilon \sim N(0, 1)$, $e \sim N(\mu, 1)$ and $\mathrm{cov}(\varepsilon, e) = \rho$. This specification gives:

$$\ln(y) \sim N[\ \ln f(.) - \mu A(.),\ B(.)] \qquad (2)$$

where $B(.) \equiv [1 + A(.)^2 - 2A(.)\rho]$. A log-likelihood function can be easily derived under this specification, and estimation can use standard nonlinear optimization methods. One implication of the SSH model is that output is distributed lognormally. Although there may be other parametric distributions that describe farm output better, the lognormal does have a history of farm output applications (*e.g.* Sherrick, *et. al*, (2004); Saha *et. al.*, (1997); Tirupattur, *et. al*. (1996)). Most importantly, Saha, *et. al.* demonstrate that marginal effects of inputs and technologies contained in g(.) on the variance of output can be either positive or negative, and independent of the marginal effects on the expected value of output. In other words, flexibility with respect to risk is achieved while retaining the damage control specification.

Two comments are worth making at this stage:

(i) With the two error terms as specified in (1), the SSH model has a resemblance to stochastic frontier models. Indeed, all damage control production functions are similar in spirit to stochastic frontier models, since both types of models posit a maximum possible output f(**x**), with firms achieving some proportion of that output. The SSH model is closer to stochastic frontier specifications, given that it incorporates two, instead of one, error terms. However, standard stochastic control specifications do not allow correlation between the two error terms.

(ii) We have started referring to marginal effects of inputs and technologies on variance, rather than on risk. As is well known, these are not generally equivalent. It is fully acknowledged here that theoretical assumptions are necessary to obtain equivalence. The first model we use, the Just-Pope production function, assumes normality of output. With this model, variance and risk effects are equivalent since the normal follows the location-scale condition of Meyer (Meyer (1989); Leathers and Quiggin (1991)). In the SSH model, output is lognormally distributed. The lognormal does not follow the location-scale condition in spite of its two-parameter nature. However, if the utility function is characterized by constant relative risk aversion (CRRA) and the random variable is lognormally distributed, Newberry and Stiglitz (1981) show that the necessary equivalence is obtained. Thus we invoke the CRRA assumption. While the assumption is open to debate (see Wik, *et. al.* (2004) and Miyata (2003) for a discussion of and evidence against this assumption in agricultural settings) we note that CRRA is often employed in analysis in agricultural economics (*e.g.* Myers (1989); Pope and Just (1991)).

III. Empirical Matters

Empirical setting

The empirical focus is on cotton growing smallholders in Makhathini flats, Kwa-Zulu Natal, South Africa (described extensively in Ismael *et. al.* (2002); Gouse, *et. al.* (2002)). About 3,000 Zulu smallholders growing rainfed cotton in Makhathini Flats, and another 500 in Tonga, in Mpumalanga together account for about 98% of smallholder cotton grown in South Africa (Hofs and Kirsten, 2002). In 1998/99, with strong support provided by a private input supply company called VUNISA, a few smallholders in Makhathini Flats started planting a Bt cottonseed variety, NuCOTN 37-B. This insecticide produced by this variety provides resistance to bollworm, which is the most troublesome class of pests in the area, followed by cotton aphids and jassids. The Bt gene, used by Delta Pineland in developing NuCOTN 37-B, belongs to Monsanto. In addition to a premium payable per bag of Bt seed over conventional seed, Bt users also pay a technology fee. At the time of the data collection for this research, VUNISA Cotton was the sole supplier of seed, chemicals and support services for the farmers through their extension officers, including credit for land preparation, chemicals and seed, based on their credit history. VUNISA bought cotton from the farmers at prices fixed by Cotton South Africa, but has faced competition from a new gin since 2002. Diffusion of the technology was very rapid in the initial years, with some estimates putting the adoption rate at

90% by 2002/03. Reports suggest that significant disadoption has occurred since then due to the removal of institutional support (credit and buy-back guarantees initially offered by VUNISA).

Agriculture is the main livelihood source in Makhathini. Smallholder farms grow between 1 and 3 hectares of rainfed cotton. Some maize and beans are grown, predominantly for subsistence, but cotton occupies the most acreage and is the main source of cash income. Smallholder cotton cultivation in the area is marked by relatively low yields. Irrigated cotton yields in China, for example, are on average in excess of 3000 kg/ha, while smallholder dry land cotton yields in Makhathini seldom exceeded 600 kg/ha prior to the introduction of Bt technology. Lack of irrigation is a major constraining factor.

Data

The dataset for the 1999-00 cotton season that we use has been discussed in detail by Thirtle *et. al.* (2003) and Shankar and Thirtle (2005), and so we restrict ourselves to a brief sketch. Survey data were originally obtained on 100 Makhatini cotton smallholders. After deletion of observations with missing values, and removal of outliers, 86 observations were used in analysis here, with 58 Bt adopters and 33 non-Bt farmers. The data included quantities of inputs and outputs, cost and revenue information for the cotton crop, as well as information on a set of socio-economic variables. Sample means for the key variables are presented in Table 1.

Table 1 about here.

Information in Table 1 reveals that Bt provided a substantial yield advantage in the year 1999-2000. It also enabled pesticide application to be lowered considerably. Note that adoption in Makhathini flats was characterized by complete adoption or non-adoption (Thirtle, *et. al.*, 2003), *i.e.* the data do not contain partial adopters. One additional aspect of interest is that the adopters on average had a significantly larger farm size. This reflects a policy adopted by VUNISA of targeting larger farmers in the early years (Shankar and Thirtle, 2005) and is further discussed below in the context of selectivity issues in estimation.

Estimation details:

All the production functions estimated in this article assume constant returns to scale and use a per-hectare specification for output and variable inputs. This is in line with most of the previous literature on Bt cotton impact assessment cited before, and also helps attenuate multicollinearity problems resulting from strong correlation between land and variable inputs such as pesticide and seed. Also, logic dictates that farm level applications of damage control models should specify at least pesticide input on a standardized (per-hectare), rather than on a whole farm basis. Since the abatement function g(z) is a proportion, expressing z on a whole farm basis would give misleading results. Henceforth, when we refer to the output y or the input sets (**x,** z), the implication is that all of these are expressed on a per-hectare basis.

The first model applied to the data is the Just-Pope production function, given by

$$y = q(z, Bt, \mathbf{x}, \boldsymbol{\alpha}) + h(z, Bt, \mathbf{x}, \boldsymbol{\beta})e,\ e \sim N(0, 1) \qquad (3)$$

Here, Bt represents a dummy variable, 1=Bt adopter, 0=non-adopter, and the rest of the notation is as before. Under this Just-Pope setup, expected value of output, E(y) = q(z, Bt, **x**), while variance of output V(y) = h^2(z, Bt, **x**), allowing all inputs as well as Bt technology to affect output variance independently of effects on the mean of output.

Cobb-Douglas forms are used in q(.) and h(.), *i.e.*

$$\begin{aligned} q(.) &= A(x_{seed})^{\alpha_{seed}}(x_{fert})^{\alpha_{fert}}(x_{lab})^{\alpha_{lab}}(z_{pest})^{\alpha_{pest}}\exp^{\alpha_{Bt}Bt} \\ h(.) &= B(x_{seed})^{\beta_{seed}}(x_{fert})^{\beta_{fert}}(x_{lab})^{\beta_{lab}}(z_{pest})^{\beta_{pest}}\exp^{\beta_{Bt}Bt} \end{aligned} \qquad (4)$$

In (4), x_{seed}, x_{fert}, x_{lab} and z_{pest} represent seed, fertilizer, labour and pesticide inputs, respectively, Bt is the Bt dummy variable, and (A, B, $\boldsymbol{\alpha}$, $\boldsymbol{\beta}$) is the parameter set to be estimated. Although the Cobb-Douglas form is restrictive, it proved to be the most practical choice for estimation here due to the relatively small sample size. Besides the problem with conserving degrees of freedom, alternative forms such as the quadratic and the translog were found to worsen extant collinearity problems.

The estimation of (3) was accomplished using the three-step process originally described by Just and Pope (1979). Suppose i indexes the farmers. First, a nonlinear least squares (NLS) regression $y_i = q(z_i, Bt_i, \mathbf{x_i}, \boldsymbol{\alpha}) + e_i^*$ was estimated, resulting in first round estimates of $\boldsymbol{\alpha}$. Given (3), this is a heteroskedastic regression. The second step involved an OLS regression of $\ln|e_i^*|$ (using e_i^* estimated from the first step) on $\ln [h(z_i, Bt_i, \mathbf{x_i}, \boldsymbol{\beta})]$, to provide estimates of $\boldsymbol{\beta}$. Finally, a NLS regression of $y_i\, h^{-1}(z_i, Bt_i, \mathbf{x_i}, \hat{\boldsymbol{\beta}})$ on $q(z_i, Bt_i, \mathbf{x_i}, \boldsymbol{\alpha})\, h^{-1}(z_i, Bt_i, \mathbf{x_i}, \hat{\boldsymbol{\beta}})$ produced revised estimates of $\boldsymbol{\alpha}$. Just and Pope (1978) show that the resultant estimates are consistent and asymptotically efficient.

The SSH model features have already been described in section II. To recap, we estimated

$$y_i = f(\mathbf{x_i}, \boldsymbol{\beta}) \exp[-A(z_i, Bt_i, \boldsymbol{\alpha})e_i]\exp(\varepsilon_i), \quad \varepsilon_i \sim N(0, 1),\ e_i \sim N(\mu, 1),\ \mathrm{cov}(\varepsilon_i, e_i) = \rho \qquad (5)$$

Saha, *et. al.* (1997) derive the loglikelihood function (LLF) for this model, given by:

$$LLF(\boldsymbol{\alpha}, \boldsymbol{\beta}, \mu, \rho) = \frac{n}{2}\ln 2\pi - \frac{1}{2}\sum_i \left\{ \ln B_i(.) + \frac{[\ln y_i - \ln f_i(.) + \mu A_i(.)^2]}{B_i(.)} \right\} \qquad (6)$$

where $B_i(.) \equiv [1 + A_i(.)^2 - 2A_i(.)\rho]$. We estimated the parameter vector ($\boldsymbol{\alpha}$, $\boldsymbol{\beta}$, μ, ρ) by maximizing (6) directly.

Alternative functional forms were experimented with for f(.) and A(.) [2], and a decision was made to use Cobb-Douglas forms for both functions. Ease of convergence in nonlinear estimation was a key factor in making this decision. Saha *et. al.* in their original application used a Cobb-Douglas form for f(.) and a linear form for A(.). Note, however, that a linear form sits uneasily with the abatement function interpretation of exp[-A(.)]. To take a simple example, if $A(z, \boldsymbol{\alpha}) = \alpha_0 + \alpha_1 z$, to keep abatement within the [0,1] interval and to have a positive marginal product for z, it would be necessary to have $\alpha_0 > 0$ and $\alpha_1 < 0$. However, the implication then is that beyond a certain value for z, A(.) would become negative, and abatement exp[-A(.)] > 1. The Cobb-Douglas form improves on the linear specification in this regard[3], and also has the virtue of parsimony.

Selectivity

Selectivity can be a serious issue in production function estimation of farm-level impacts of a technology using cross-sectional data. While survey datasets such as the one used in this research may contain information on both adopter and non-adopters, there is usually no random assignation of individuals into such groups. There is then the very real possibility that adoption patterns of individuals are related to their productivity patterns. Often, 'better' or more efficient farmers, who are able to get more output out of a given technology and a given set of inputs, are also the ones to adopt technologies that improve productivity. Thus production function estimation using cross-sectional data is likely to exaggerate the impacts of technology adoption, confounding the inherent efficiency of adopting farmers with the actual performance of the technology itself.

Selectivity is an issue to be considered seriously in farm-level GM crop impact estimation as well. However, there has been surprisingly little explicit attention devoted to this issue in the literature. Where panel data are available, it is possible to control for farmer-specific effects, thereby isolating the technology effects accurately. In a cross-sectional context, one solution is to use Heckman's correction, where inverse Mills ratios derived from first step adoption probit models can be used to correct selectivity bias in second step production function estimation. A common problem with this strategy, however, is that instruments derived from adoption probits are often poor.

However, as Barnow, Cain and Goldberger (1980) point out, assuming the effects that cause the sample selection problem are observable, including those variables in the outcome regression would correct for the sample selection problem. This standard regression based method has been called 'ignorability of treatment' (Rosenbaum and Rubin, 1983), and 'selection on observables' (Heckman and Robb, 1985) in the literature. Loosely, treatment is random/ignorable conditional on those variables that affect both selection and outcomes. In Makhathini, Shankar and Thirtle (2005) have argued that farm size was the main variable determining adoption. VUNISA launched the technology by promoting it to larger farmers in the initial years, with the expectation that smaller farmers would be picked up via copy adoption in later years. Indeed, farm size was the only strongly significant variable in adoption models reported by Thirtle *et. al.* (2003) and Shankar and Thirtle (2005). Thus, inclusion of a farm size variable in our production function regressions may be an effective control for any existing selectivity. Other socio-economic variables such as farmer education and age have also been used in production functions estimated in the Bt cotton literature (*eg.* Qaim 2003; Qaim and de Janvry, 2005). A similar set was used in initial runs in this research. However, these other variables were largely insignificant in all regressions. The farm size variable alone was retained in the final set of estimates, because of farm size being a potential determinant of yields and also because of its role in selectivity control.

IV. Results

Just-Pope production function results

As noted before, the first step (mean) regression in the three-step procedure is implicitly a heteroskedastic regression. We therefore tested for heteroskedasticity in the first step. Two tests were carried out, White's (1980) test and Breusch & Pagan's (1979) test. In both tests, the test statistic is distributed as chi-squared under the null hypothesis of no heteroskedasticity. The White test makes no assumptions about the form of the heteroskedasticity and simply tests H_0: $\sigma^2_i = \sigma^2$ for all i against H_1: Not H_0. The Breusch-Pagan test on the other hand is a Lagrange multiplier test that assumes that if any heteroskedasticity exists, the error variance varies with a set of regressors. In our case, the natural set of regressors to use is the set of regressors used in the variance regression step of the Just-Pope function, *i.e.*, a constant, the three variable inputs, farm size, and the Bt adoption dummy. The White test value was 56.82, which is considerably in excess of the 95% level chi-square critical value of 38.80. Thus the White test strongly rejects the null hypothesis of homoskedasticity. The Breusch-Pagan test value was 25.83, which is also substantially higher than the 95% level chi-square critical value of 11.07 with 5 degrees of freedom. The Breusch-Pagan test thus bolsters the evidence provided by the White test that the null hypothesis of homoskedasticity can be rejected, and provides further rationale for the investigation of how output variance or risk is affected by inputs and technology.

Table 2 presents the estimates of the mean and variance portions of the Just-Pope production function, following implementation of the three-step procedure outlined earlier. Even though the mean portion is estimated as a Cobb-Douglas function with an additive, instead of the usual exponential error term, it retains an elasticity interpretation. Thus the elasticities of expected value of yield with respect to the variable inputs are all positive and have plausible values, although the seed elasticity is insignificant. Increasing farm size is seen to have a depressing effect on the expected value of yields, although the parameter is significant only at the 10% level. The Bt dummy variable parameter is the most strongly significant of all, and the positive value confirms previous findings that Bt varieties provide a strong boost to (expected value of) yields.

Table 2 about here.

The variance effects of the inputs, seen in the bottom half of the table, are however far weaker as estimated by the Just-Pope model. A positive (negative) coefficient sign indicates a risk increasing (decreasing) effect for the input it is attached to. Seed is seen to be the only variable input with a statistically significant effect on output variance, and that only at the 10% level. The positive sign of the pesticide coefficient indicates a risk increasing effect for the input. However, it is insignificantly different from zero. The Bt dummy on the other hand, bears a negative sign indicating a risk-decreasing effect, but is even more strongly insignificant. Opposing signs for the pesticide and Bt dummy are not in line with expectations[4], and along with the very low t-ratios suggest that the Just-Pope model cannot confirm any strong evidence for the hypothesis that Bt technology reduces risk.

However, noting again that the Just-Pope function is estimated only as a preliminary step in the investigation of risk properties, and that it does not have a damage control specification appropriate for the pesticide and Bt variables, we now turn to results obtained from the SSH model.

SSH model results

Table 3 presents results from the SSH model. For comparison, we also present results from a damage control model obtained by imposing restrictions on the SSH model in (5), *i.e.*,

$$y_i = f(\mathbf{x_i}, \boldsymbol{\beta}) \exp[-A(z_i, Bt_i, \boldsymbol{\alpha})]\exp(\varepsilon_i), \quad \varepsilon_i \sim N(0, \sigma^2) \qquad (7)$$

With its single error term specification, potential output function f(.) and abatement function exp[-A(.)], (7) is a traditional damage control function. It can allow only risk-increasing inputs and technologies, in contrast to the SSH model, (5), which allows the data to determine the risk effects of inputs and technologies. This damage control model was estimated using nonlinear least squares.

Table 3 about here

The labour and seed production elasticities from the two models, seen in the top half of Table 3, are not substantially dissimilar to the mean function estimates produced previously by the Just-Pope model. However, the SSH model produces a somewhat lower and statistically insignificant estimate for the seed coefficient, 0.16, compared to the significant 0.22 under the damage control model. The farm size effect is seen to be indistinguishable from zero under both models. An obvious *a-priori* expectation is that pesticide input and Bt technology should not reduce abatement. Equivalently, $\partial y/\partial z_{pesticide} \geq 0$ and $(y|_{Bt} - y|_{NonBt}) \geq 0$, all else held equal. For these to hold, it can be verified that the coefficients attached to pesticide input and the Bt technology dummy in the two models need to be non-positive. As can be seen from the table, this is indeed so. In both models, the negative valued coefficients $\alpha_{pesticide}$ and α_{Bt} are also significant at conventional significance levels, although these coefficients seem more precisely measured with the damage control model.

As Saha, *et. al.* note, a necessary condition for rejecting the SSH model in favour of the damage control one is the restriction ρ=0 where ρ is the covariance between the two random variables e and ε, since one of the random variables is missing in the damage control model. Table 3 shows that the estimated value of ρ is highly significant, with a t value of 25.89. Thus we cannot find evidence to support discarding the SSH model in favor of the simpler damage control model. ρ has a positive value of 0.86. This positive correlation between pest density random variable e and rainfall random variable ε would appear to contradict the earlier notion that e and ε should be negatively correlated. However, this is misleading. It can be calculated from (5) that $\partial y/\partial \varepsilon > 0$, *i.e.*, the rainfall random variable is ordered from bad states of nature (poor rainfall) to good states (good rainfall). However, $\partial y/\partial e < 0$, *i.e.*, the pest density random variable is ordered from good states of natures (low pest density) to bad (high pest density) in the SSH model (5). Therefore, ρ should indeed be positive. Our finding of a positive, strongly significant value for ρ is thus consistent with the earlier interpretation of the two random variables in the model, and lends support for the SSH model in comparison to a simpler damage control alternative.

The mean and variance effects of pesticide input and Bt technology were calculated at the sample mean values of the variables. At the baseline, it was assumed that non-Bt technology was being used, and all other independent variables were being held fixed at overall sample mean values. Given this baseline, the pesticide effects were calculated as $\partial E(y)/\partial z_{pesticide}$ and $\partial V(y)/\partial z_{pesticide}$, *i.e.*, the marginal effects on expected yields and yield variance[5] of a one unit increase in pesticide. The Bt technology effect is a discrete one, where the technology provides the equivalent of an unknown number of units of pesticide upon adoption. Thus the Bt effects were calculated as $E(y)|_{Bt} - E(y)|_{Non\text{-}Bt}$ and $V(y)|_{Bt} - V(y)|_{Non\text{-}Bt}$, with all other variables held fixed. These effects were calculated for both the damage control model and the SSH model. Approximate standard errors were also calculated using the Delta method. The results are reported in Tables 4 and 5.

Table 4 about here.

Table 5 about here.

Both models in Table 4 are seen to predict a positive and statistically significant effect of pesticide on expected yields. Indeed, these effects are almost identical across the models. Turning to the variance effects of a marginal increase in pesticide use, the damage control model predicts an increase in the variance (risk). As discussed earlier, this is as expected, since the damage control model forces the variance effect to be in the same direction as the marginal product. However, the SSH model, which provides flexible risk effects, predicts the same qualitative risk effect, *i.e.* that pesticide increases risk. In fact, the increase in yield variance is significantly higher in the SSH model than in the damage control model, in response to the same marginal unit increase in pesticide.

Since Bt technology embodies a certain type of pesticide, the expectation is that the mean and variance effects of Bt technology adoption would be along the same lines as those for pesticide. This is verified in Table 5. Once again, the mean effects of Bt technology adoption are positive, strongly significant, and almost identical across the two models. Since Bt technology is likely to provide the equivalent of several litres of bollworm pesticide during the season, the technology effect is much stronger than that of a marginal unit of pesticide seen in Table 4. Under the damage control model, the variance effect of Bt technology is positive, *i.e.* risk-increasing, as expected. However, again the SSH model reaffirms this qualitative finding in a flexible risk setting. Under the SSH model, Bt technology adoption is found to increase risk. What is more, the increase predicted by this flexible risk model is more than ten times the quantitative increase found under the damage control model. Although there is some imprecision in the estimation of this effect under the SSH model, the effect is nevertheless significant at the 10% level.

Thus neither the Just-Pope model nor the SSH model is able to confirm a strong and statistically significant risk-decreasing effect for Bt technology. Therefore, the available evidence does not allow claim of this potentially valuable additional benefit for the technology in Makhathini. On the contrary, the SSH model predicts a strong risk-increasing effect. This is intuitively plausible given the bioeconomic theory of pesticide and risk discussed previously. We have noted before that cotton cultivation in Makhathini is rainfed, and that lack of irrigation is a major constraining factor. Under these circumstances, rainfall is likely at least as important a source of randomness as pest density. Where rainfall is relatively low, there is less crop to protect, and Bt technology is relatively less effective. Where rainfall is relatively high, there is more crop to protect, and the technology is more effective in raising marginal cotton product. In other words, the technology in these circumstances is a 'fair weather friend'. Even where the rainfall and pest density random variables are strongly negatively correlated in the Horowitz and Lichtenberg sense (strongly positively correlated from the SSH model perspective), Horowitz and Lichtenberg have shown that a risk increasing effect is likely. This strong correlation has been confirmed for our case, and is consistent with the risk increasing effect we find.

V. Conclusion

This research has investigated an important, but previously unexplored, aspect of GM technology – it's production risk aspects. Specifically, we have been interested in testing the hypothesis that Bt cotton technology reduces risk in South Africa, in addition to the (expected) yield-boosting effect measured and analyzed by previous studies. The risk notion is of importance in a developing country smallholder setting since small farmers have relatively few avenues available to shift risk. The risk aspect is also intimately tied up with notions of vulnerability that are given much prominence in the poverty literature.

Our review of the bioeconomics of pesticide and risk revealed that the risk effects of this technology can be hard to predict and are probably situation-dependent. Where multiple sources of uncertainty abound, such as rainfall and pest-density, depending on the relative importance of each random variable and the correlation between them, either risk-increasing or risk-decreasing effects can plausibly be found. The first model applied was a Just-Pope model that is the workhorse of production risk investigation. In accordance with the notion of multiple sources of randomness, we also chose to apply the SSH production function model that can display flexible risk effects in addition to accommodating two distinct sources of randomness and a damage control representation.

Our results showed that neither model can provide any support for the risk-reduction hypothesis. The Just-Pope model shows the risk effect of Bt technology to be insignificant, while the SSH model shows a strong, statistically significant risk-increasing effect. This is consistent with the notion of rainfall being a key source of randomness in irrigated smallholder cotton production. Thus a plausible interpretation of the results is that Bt technology best produces its effects in Makhathini when the going is good, *i.e.*, when the crop-growth conditions (rainfall) are good.

It must be emphasized that this research is just one preliminary piece in a potentially larger puzzle concerning GM technology and production risk. There are a number of limitations to this study, and there is much scope for future investigation. Firstly, risk effects are almost certainly situation dependent, and so similar applications to other parts of the world are warranted. Secondly, we have only used cross-sectional data[6], and further analysis with panel data models can provide richer specifications controlling for heterogeneity and selectivity, if present. To provide an example of how panel specifications might be important, note that one potential cause of correlation between the random variables e and ε is individual heterogeneity. Lacking panel data, we have been unable to control for such heterogeneity and have simply interpreted the correlation in terms of natural production randomness. The Bt cotton evaluation literature has thus far avoided proper panel-data analysis, even where such data were available, possibly because of the difficulty of including heterogeneity effects within nonlinear models such as the damage control ones commonly applied. However, multiplicative panel data models (Wooldridge, 1997) have potential in this regard, and Carpentier and Weaver (1999) have shown how these can be adapted to damage control models. Thirdly, we have only calculated the risk effects of the technology, but have not been able to further explore implications for the smallholders. This is due to a lack of data for this study, but where household wealth data are available, it is possible to compute welfare equivalents of the increased risk for individuals in the data set or for representative agents.

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Table 1. Summary Statistics by Adoption Category, 1999/2000

	Non-adopters		**Adopters**	
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**
Output (kg)	1293.5	1644.2	2200.0	1533.8
Labour (days)	18.5	8.5	22.0	9.1
Seed (25 kg bags)	1.9	1.3	2.2	2.1
Pesticide (litres)	8.6	8.5	7.2	6.3
Land (hectares)	3.9	2.9	6.1	5.8
Age (years)	44.4	10.3	46.6	8.3
Farmsize (hectares)	4.8	3.4	7.3	6.0
Yield (kg/ha)	330.3	206.3	482.9	252.8
Labour per ha. (days/ha)	6.1	4.4	5.8	3.9
Seed per ha (bags/ha.)	0.6	0.3	0.5	0.3
Pesticide per ha (litres/ha)	2.4	1.2	1.6	1.0

Table 2. Just-Pope Production Function Estimates±

Parameter	Estimate	t Value
Mean Regression		
$\alpha_{farmsize}$	-0.11	-1.67*
α_{labour}	0.25	2.44**
α_{seed}	0.20	0.87
$\alpha_{pesticide}$	0.20	2.00**
α_{Bt}	0.12	4.77***
Variance Regression		
$\beta_{farmsize}$	-0.01	-0.06
β_{labour}	-0.04	-0.15
β_{seed}	0.44	1.74*
$\beta_{pesticide}$	0.15	0.75
β_{Bt}	-0.06	-0.24

± * implies significance at 10% level, ** at 5% level, *** at 1% level.

Table 3. SSH model estimates±

	Damage Control Model		SSH Model	
Parameter	Estimate	t Value	Estimate	t Value
β_{labour}	0.25	2.28**	0.24	1.78*
β_{seed}	0.22	1.91*	0.16	1.28
$\beta_{farmsize}$	-0.03	-0.35	-0.03	-0.29
$\alpha_{pesticide}$	-0.25	-2.86***	-0.29	-1.83*
α_{Bt}	-0.87	-3.57***	-0.58	-2.43**
σ	0.49	12.57***		
ρ			0.86	25.89***
μ			0.24	1.82*

± * implies significance at 10% level, ** at 5% level, *** at 1% level

Table 4. Mean and Variance Effects of Pesticide±

	Mean Effect: $\partial E(y)/\partial z_{pesticide}$	Variance Effect: $\partial V(y)/\partial z_{pesticide}$
Damage control model	0.036 (0.0001)	0.006 (0.00001)
SSH model	0.040 (0.002)	0.040 (0.009)

± Approximate standard errors in parantheses.

Table 5. Mean and Variance Effects of Bt Technology[±]

	Mean Effect: $E(y)\|_{Bt} - E(y)\|_{Non\text{-}Bt}$	**Variance Effect:** $V(y)\|_{Bt} - V(y)\|_{Non\text{-}Bt}$
Damage control model	0.215 (0.004)	0.049 (0.0007)
SSH model	0.213 (0.019)	0.610 (0.336)

± Approximate standard errors in parantheses.

Endnotes

[1] Other dimensions of risk, such as price and marketing risk associated with Bt technology are recognised as important, but are beyond the scope of this paper.

[2] Saha, *et. al.* (1997) also argued that a case can be made for including 'conventional' inputs such as labour in the A(.) function since they may also have a damage abating role. We tried including other variable inputs in A(.) but they were strongly insignificant and were therefore dropped.

[3] Stochastic frontiers are more effective in ensuring that the proportion of potential output achieved stays within [0.1], by having a truncated distribution specification for the achieved proportion. They would be good candidates for modelling the problem specified here. However, the introduction of the correlation between the error terms complicates stochastic frontier estimation very considerably, as can be verified.

[4] It is possible that occasional events like rainfall wash-off of pesticide can cause the technology and conventional pesticide application to have different qualitative risk effects. This is likely to be an exception rather than a rule, however.

[5] Although the summary statistics table expresses output and yields in kilograms, the original dataset expressed these in bales of 200 kgs each. The latter unit, *i.e*, bales were used during econometric estimation. Those interested in the quantitative values of these estimates should multiply by 200 to get values in kilograms.

[6] Another year of data (1998-99 season) for these Makhathini smallholders are available, as detailed in Thirtle *et. al.* (2003). However, this first year of data was collected more than one year in retrospect, *ie*, after the 1999-2000 season, jointly with data collection for 1999-2000. In our judgement, these data from long recall were almost surely too inaccurate to be worthy of inclusion in the analysis here.